Development of the Integrated Rural Access Index (iRAI) using Remote Sensing and GIS

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Abstract

This study proposes an improvement to the measurement of Sustainable Development Goal (SDG) Indicator 9.1.1 which quantifies the proportion of the rural population living within 2 kilometers of an all-season road through the development of the Integrated Rural Access Index (iRAI). While the conventional Rural Access Index (RAI) measures solely road proximity, it fails to incorporate access to essential services. To address this limitation, the iRAI integrates the proximity to three critical facilities – healthcare, education, and service – using data from the Philippine Statistics Authority's Community-Based Monitoring System. Gridded population datasets from WorldPop and LandScan were evaluated to determine suitability for computing RAI and iRAI. WorldPop demonstrated superior performance, with a lower mean absolute error (MAE = 18.60), root mean square error ($RMSE$ = 36.41), and a higher correlation coefficient (r = 0.94), and was thus used for calculating both RAI and iRAI. In the provinces of Cavite and Batanes, Sentinel-2 imagery and Maximum Likelihood Classification (MLC) were utilized to delineate rural boundaries. Error metrics (MAE = 0.52, $RMSE$ = 0.65) show strong agreement and practical interchangeability between conventional and satellite-based RAI/iRAI values. Regression analyses revealed that the iRAI exhibited stronger explanatory power (R^2 = 0.4878) and statistical significance (p = 0.0396) compared to RAI. A scenario simulation suggested that improvements in poverty, education, and healthcare access could result in a perfect iRAI score. Additionally, a network-based methodology was developed and applied in three areas to overcome the limitations of planar distance, demonstrating the potential for more accurate, household-level accessibility assessments.

1. Introduction

In 2015, 193 UN member states adopted the 2030 Agenda for Sustainable Development, comprising 17 Sustainable Development Goals (SDGs) aimed at promoting global dignity, peace, and prosperity. This study centers on SDG 9, which advocates for resilient infrastructure, inclusive industrialization, and innovation. Specifically, it focuses on Target 9.1 and Indicator 9.1.1, defined as the proportion of the rural population living within 2 km of an all-season road, a metric critical for measuring equitable access to infrastructure. The Rural Access Index (RAI), developed by Roberts et al. (2006), serves as a global standard for evaluating rural transport accessibility, aligning directly with SDG Indicator 9.1.1. An all-season road, as defined by the same authors, is one that remains passable year-round with minimal interruption, especially on low-volume roads. While the RAI is widely used for policy and planning, it primarily measures proximity to roads, overlooking broader dimensions of access to essential services. This study addresses this limitation by enhancing the RAI through integration with data from the Community-Based Monitoring System (CBMS), implemented under Republic Act No. 11315 in the Philippines. Administered by the Philippine Statistics Authority (PSA), the CBMS provides localized, disaggregated data that includes geotagged information on households and critical facilities such as health centers, hospitals, schools, public markets, and evacuation centers. Incorporating these facilities into the RAI framework enables a more holistic assessment of rural accessibility, especially in deprived communities. The primary objective of this study is to develop an Improved Rural Access Index (iRAI) that better reflects access to both road infrastructure and critical facilities. This approach can inform evidence-based planning and decision-making by local government units (LGUs), ultimately improving infrastructure provisioning and service delivery in underserved rural areas.

2. Methodology

This study aims to enhance the 2016 World Bank (WB) RAI by integrating key critical facilities data from the CBMS. The enhanced methodology, referred to as the Improved RAI (iRAI), assesses rural population accessibility not only to all-season roads but also to essential services in healthcare, education, and public infrastructure. The approach was applied nationwide to all rural areas in the Philippines classified under the 2020 Census of Population and Housing (CPH), with comparative analysis highlighting provinces with the highest and lowest RAI and iRAI scores.

2.1 Data

Key datasets (Table 1) were collected from national and open-source platforms and evaluated for completeness and spatial accuracy. Urban-rural classified barangay boundaries were derived from the 2020 CPH by the PSA. These boundaries were used to spatially disaggregate indicators and define the rural extent. Satellite imagery underwent atmospheric correction and supervised classification to extract built-up areas and delineate rural boundaries more accurately. Road network data from OSM was reviewed and validated using random spot checks to verify accuracy. CBMS data were filtered to extract geotagged locations of essential critical facilities, such as healthcare centers, schools, and service institutions.

Furthermore, data processing generated rural population rasters and applied 2-km buffers around road networks and critical facilities. These buffers were intersected to identify the population with dual access. Zonal Statistics were then used in the final phase to compute the RAI and iRAI, allowing comparative analysis across methodologies and correlation with socioeconomic indicators

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2.2 Methods

The study employed a four-phase approach: Data Collection, Pre-Processing, Data Processing, and Post-Processing and Evaluation (Fig. 1).

Dataset	Source	Year	Type
100m WorldPop Gridded Population Data (GPD)	WorldPop Project	2020	Gridded Population
1 km LandScan GPD	Oak Ridge National Laboratory	2020	Gridded Population
Sentinel-2 Level-2A	Copernicus	June 2020	Multispectral Satellite Imagery
Urban-Rural Boundaries	CPH, PSA	2020	Administrative Layer
OSM Road Network	OpenStreetMap	NA	Line
CBMS Facilities	CBMS, PSA	2022-2023	Point
CBMS Households	CBMS, PSA	2022-2023	Point

Table 1. Datasets for RAI and iRAI calculation.

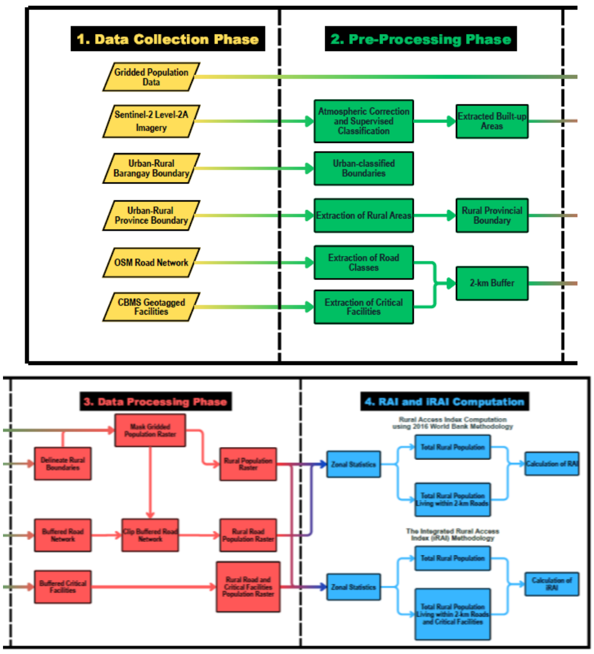

Figure 1. Methodology of this study.

2.2.1 Rural Access Index Computation Using 2016 World Bank RAI Methodology: The WB RAI methodology was implemented using QGIS through a five-step process: 1) defining rural boundaries, 2) extracting rural population rasters, 3) generating 2-km buffers around roads, 4) identifying rural populations within these buffers, and 5) computing the RAI. Barangay boundaries with urban-rural classification were used to exclude rural areas, yielding rural-classified provincial polygons. These were intersected with the WorldPop 100-m gridded population data to derive rural population rasters. Road networks were buffered by 2 km to establish zones of accessibility. The rural population within these buffered road zones was then quantified using QGIS Zonal Statistics. RAI was calculated per province using the standard WB formula in Equation 1.

$$WB\ RAI = \frac{TRP_{2km}}{TRO} \times 100 \quad (1)$$

where TRP_{2km} = total rural population living within 2 km from all-season road
TRP = total rural population

This process enabled spatial assessment of rural access at the provincial level and served as a baseline for comparison with the iRAI methodology.

2.2.2 The Improved Rural Access Index Methodology: For LandScan, the Philippine extent was extracted and intersected with rural classified provincial boundaries. These boundaries were further refined to include only LGUs with available PSA-led CBMS facility data. Three categories of critical facilities: education, healthcare, and service were extracted from CBMS data and buffered by 2 km, along with the previously buffered road networks. These buffers were overlaid on the gridded population datasets to estimate the rural population within proximity to both road infrastructure and critical facilities.

2.2.3. Gridded Population Raster Data for iRAI Computation: Similar to the 2016 WB methodology, gridded population datasets were initially used to compute the enhanced iRAI. However, in this methodology, the 2020 gridded population distribution data with 1-km resolution from LandScan was utilized as an additional source for calculating the iRAI. Since the LandScan data covered the entire world, the extent of the Philippines was extracted from the dataset. Next, the rural population was identified from the LandScan data by extracting the rural provincial boundary layer. Furthermore, since the current PSA-led CBMS operations only covered several cities/municipalities around the country and not all these LGUs have transmitted their CBMS facilities data yet, the previously created rural-classified provincial boundary used to generate the WB RAI needed to be trimmed further to highlight only those cities/municipalities with available CBMS data. The iRAI scores were computed per facility component using the following formulas in Equations 2, 3, and 4:

$$iRAI^{EF} = \frac{TRP_{2km} \cap EF_{2km}}{TRP} \times 100 \quad (2)$$

$$iRAI^{HF} = \frac{TRP_{2km} \cap HF_{2km}}{TRP} \times 100 \quad (3)$$

$$iRAI^{SF} = \frac{TRP_{2km} \cap SF_{2km}}{TRP} \times 100 \quad (4)$$

where TRP = total rural population
TRP_{2km} = total rural population living within 2 km from all-season road
EF_{2km}, HF_{2km}, SF_{2km} = total rural population living within 2 km of educational, healthcare, and service facilities, respectively.

This approach enabled a more refined assessment of rural accessibility by integrating infrastructure and social service availability into the traditional RAI framework.

2.2.4 Extraction of Built-up Areas from Sentinel-2 Imagery: Built-up areas were derived from Sentinel-2 imagery to support RAI and iRAI computation in selected pilot provinces – Batanes

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and Cavite, representing high and low scores, respectively, based on preliminary analysis using gridded population data. Both provinces were also selected due to the availability of CBMS facility data essential for computing iRAI. Sentinel-2 Level-2A images dated June 2020 were acquired via the Copernicus Open Access Hub. Satellite images were masked and mosaicked to generate a seamless composite for each province, followed by atmospheric correction using ENVI's Quick Atmospheric Correction (QUAC). Land cover classification was performed using Maximum Likelihood Classification (MLC), based on three classes: Built-up, Vegetation, and Bare Land. Training samples for each class were manually collected from the imagery to support robust classification. Accuracy assessment was conducted using reference data points from 2020 Google Earth imagery, due to limited capacity for field validation. Validation points were randomly selected for all land cover classes, and accuracy metrics were calculated to assess classification reliability. Moreover, only the built-up class was retained for further analysis. These built-up areas were subtracted from the non-administrative boundaries to delineate rural areas within each province, which were then used to mask WorldPop population data to derive rural population raster datasets (Fig. 2). These datasets formed the basis for computing RAI and iRAI using the established methodology.

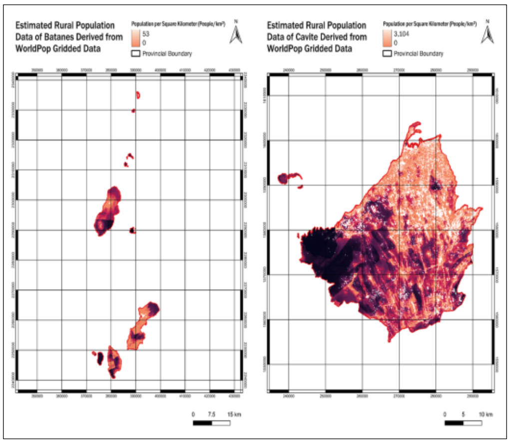

Figure 2. The Estimated Rural Population of Batanes (left) and Cavite (right) Derived from WorldPop Gridded Population Raster Data.

2.2.5 Network-Based Household-level RAI and iRAI: The traditional RAI methodology estimates the share of the rural population living within 2 km of roads using Euclidean distance buffers. While efficient, this approach fails to account for actual travel constraints, such as road connectivity, natural terrain, or physical barriers. To address this limitation, a network-based RAI and iRAI approach was developed. This method leverages the road network to compute access distances, thereby offering a more realistic depiction of rural accessibility conditions. The use of network analysis allows for a better estimation of accessibility costs and travel difficulty, providing more refined and actionable insights for infrastructure planning. This study implemented the network-based RAI (NB-RAI) and network-based iRAI (NB-iRAI) using household-level geotagged data from the CBMS, in conjunction with OSM road networks and CBMS critical facilities. Three localities were selected for analysis, based on earlier computed RAI and iRAI scores and findings from rural accessibility studies: 1) the City of Tayabas, Quezon Province, identified by Cucio et al. as having barangays with severe accessibility deficits; 2) the Municipality of San Jose, Dinagat Islands, which recorded the highest iRAI value; and 3) the Municipality of Northern Kabuntalan, Maguindanao del Norte, with the lowest RAI value. Network analysis was conducted using the QNEAT3 plugin in QGIS. The plugin's Origin-Destination (OD) Matrix Analysis tool was applied to compute the shortest travel distance between each household and the nearest road segments, constrained to a 2-km threshold consistent with the standard RAI definition. Where households had multiple possible road connections, only the shortest proximity was retained, representing the most direct network-based access. Following this, spatial joins were performed to associate each household with its corresponding rural boundary at the city or municipal level. The NB-RAI and NB-iRAI values were then computed using modified versions of the original indices using the formulas in Equations 5 and 6:

$$NB\ RAI = \frac{TRH_{2km}}{TRH} \times 100 \tag{5}$$

$$NB\ iRAI^{o} = \frac{TRHCF_{2km}}{TRH} \times 100 \tag{6}$$

where TRH = total number of geotagged rural households
TRH_{2km} = number of geotagged rural households located within 2 km of road, based on network analysis
$TRHCF_{2km}$ = number of geotagged rural households located within 2 km of both road networks and critical facilities

3. Results and Discussion

3.1 Comparative Analysis between WorldPop and LandScan Gridded Population Raster Datasets

A comparative analysis was conducted to assess the suitability of WorldPop and LandScan datasets for rural accessibility studies. Provincial population estimates derived from each raster dataset were compared against the official 2020 Census data from the PSA, using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Pearson Correlation Coefficient (CC) as evaluation metrics. WorldPop, with its finer 100-meter resolution, showed better performance, recording an MAE of 18.60, RMSE of 36.41, and a CC of 0.94. In contrast, LandScan exhibited higher error values (MAE = 42.27, RMSE = 81.53) and a lower CC of 0.70. These results indicate that WorldPop estimates are closer to actual census figures and better capture spatial population distribution. Overall, WorldPop offers more accurate and consistent population estimates, making it more suitable for fine-scale analyses such as RAI and iRAI computation in rural areas.

3.2 The 2016 World Bank RAI Methodology

Using the 2020 WorldPop gridded population dataset, provincial-level RAI scores were computed following the World Bank methodology. High RAI values, close to 100, indicate a strong rural access to roads, while low scores suggest limited or poor-quality road infrastructure. Roberts et al. (2006) reported an average RAI of 57% for over 30 International Development Association (IDA) countries, with Sub-Saharan Africa averaging 30%. Non-IDA countries averaged nearly 90%. Timor-Leste, for example, set a national target RAI of 90% by 2030 (Eqbali et al., 2017), reflecting its development priorities. While no global target exists, an RAI of 90% or higher is generally regarded as a strong benchmark. In the Philippines, approximately 82% of provinces meet or exceed this 90% threshold. Siquijor achieved a perfect RAI of 100%, followed by La Union (99.92%), Cavite (99.88%), Guimaras (99.76%), and Batangas (99.68%). In contrast, Maguindanao del Norte recorded the lowest RAI of 64.05%, with other low-scoring provinces including Rizal

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(67.29%), Occidental Mindoro (74.02%), Tawi-Tawi (76.66%), and Apayao (77.37%).

3.3 The iRAI Methodology

3.3.1 Gridded Population Raster Data: Based on the WorldPop dataset, Biliran recorded the highest $iRAI^{HF}$ at 91.46%, followed by Dinagat Islands (88.89%), Camiguin (88.30%), Quirino (80.79%), and Abra (76.79%). These values indicate strong rural access to both roads and healthcare facilities. Conversely, Occidental Mindoro had the lowest $iRAI^{HF}$ at 0.50%. Other provinces with limited rural access to healthcare include Nueva Ecija (1.57%), Bataan (1.74%), Davao del Sur (3.87%), and Davao Oriental (5.73%).

Biliran recorded the highest $iRAI^{EF}$ at 93.69%, followed by Dinagat Islands (91.02%), Camiguin (90.02%), Quirino (87.97%), and Abra (86.41%). These results indicate strong rural access to educational facilities, complementing Biliran's high healthcare accessibility. Moreover, Occidental Mindoro had the lowest $iRAI^{EF}$ at 0.65%, with similarly low values in Nueva Ecija (1.65%), Bataan (1.82%), Davao del Sur (4.24%), and Tawi-Tawi (5.45%). Notably, provinces with poor education access also had low healthcare access, highlighting persistent service gaps in these areas.

Dinagat Islands recorded the highest $iRAI^{SF}$ with 70.23%. Other provinces with high scores include Aurora (59.69%), Abra (59.60%), Quirino (59.13%), and Batanes (58.41%). Furthermore, this is the only component where Biliran (56.18%) did not top the rankings. These results reflect strong rural access to both roads and essential service facilities, such as public markets and evacuation centers. Such infrastructure supports community resilience during emergencies and promotes local economic activity.

According to Project for Public Spaces (n.d.), public markets bridge urban and rural economies, fostering stronger social and economic ties that contribute to balanced development and disaster resilience. Consistently, Occidental Mindoro recorded the lowest $iRAI^{SF}$ value at 0.69%, followed by Davao Oriental (1.34%), Nueva Ecija (1.53%), Davao del Norte (1.61%), and Bataan (1.71%). The consistently low iRAI scores in Occidental Mindoro highlight persistent rural accessibility challenges. In these provinces, rural communities may face difficulties accessing essential goods, services, and economic opportunities due to limited infrastructure or remote locations.

To determine the overall rural accessibility, a composite iRAI was computed using the WorldPop gridded population dataset and the spatial intersection of critical facilities with roads. The formula used for calculating the overall index is presented in Equation 7:

$$iRAI^{O} = \frac{TRP_{2km} \cap HF_{2km} \cap EF_{2km} \cap SF_{2km}}{TRP} \times 100 \quad (7)$$

The results identified Dinagat Islands as the province with the highest overall accessibility (68.84%), followed by Aurora (57.49%), Quirino (56.92%), Camiguin (56.06%), and Abra (55.31%). These provinces demonstrate relatively strong alignment between population distribution, road infrastructure, and critical facility services. Conversely, Occidental Mindoro recorded the lowest overall iRAI (0.39%), with other low-scoring provinces including Davao Oriental (1.28%), Nueva Ecija (1.37%), Davao del Norte (1.53%), and Bataan (1.71%). An analysis of component-specific iRAIs showed similar trends. Biliran and Dinagat Islands consistently ranked among the highest across all components, indicating effective spatial coverage of healthcare, educational, and service infrastructure. In contrast, provinces with consistently low scores exhibited limited facility coverage and poor spatial distribution, often concentrated in only a few municipalities. Notably, data completeness emerged as a critical factor. Only 690 of 1,642 LGUs had participated in CBMS during the 2021-2023 period. Provinces with full participation, such as Dinagat Islands and Camiguin, achieved higher scores, whereas provinces with limited CBMS data exhibited significantly reduced iRAI values (Fig. 3).

To assess this impact, recalculated overall provincial iRAI scores ($iRAI^{O\text{-}2}$) were computed using only municipalities with complete CBMS data (Table 2). Results showed substantial increases in accessibility scores. For instance, Bataan's iRAI rose by 98.31 percentage points when excluding non-participating LGUs, while Nueva Ecija and Occidental Mindoro also recorded significant improvements. This pattern emphasizes the sensitivity of iRAI results to missing geospatial data.

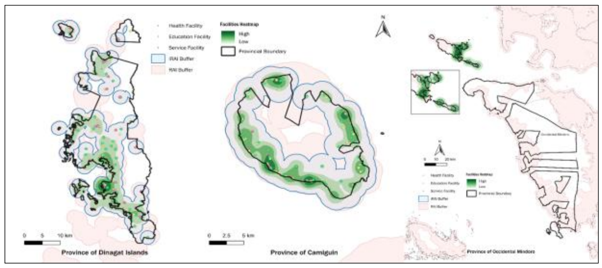

Figure 3. Critical Facilities of the Provinces of Dinagat Islands (left), Camiguin (middle), and Occidental Mindoro (right).

Province	$iRAI^{O-1}$	$iRAI^{O-2}$	Percentage Points Increase
Bataan	1.69	100	98.31
Davao del Norte	1.53	39.07	37.54
Nueva Ecija	1.37	95.32	93.95
Davao Oriental	1.28	25.78	24.50
Occidental Mindoro	0.39	55.96	55.57

Table 2. The original iRAI Scores ($iRAI^{O\text{-}1}$) of Bottom Five Provinces Compared to their Recalculated Provincial-level Overall iRAI ($iRAI^{O\text{-}2}$).

Furthermore, spatial distribution rather than facility counts alone significantly influenced accessibility. Provinces such as Camiguin and Dinagat Islands, despite having fewer facilities, achieved high scores due to efficient spatial dispersion relative to small rural populations. In contrast, provinces like Abra and Aurora, with greater facility counts but clustered distributions, resulted in lower iRAI scores.

3.3.2 Extracted Built-up Areas from Sentinel-2 Images: An alternative method for estimating RAI and iRAI was tested in the provinces of Batanes and Cavite, using Sentinel-2 imagery to delineate built-up areas through Maximum Likelihood Classification (MLC). This replaced reliance on administrative urban-rural classifications with a more dynamic, image-based delineation of rural zones. The extracted built-up areas were masked with provincial boundaries to generate rural population rasters using WorldPop. Accuracy assessment using confusion matrices yielded an overall accuracy of 86.43% and a kappa of 0.70 for Batanes, and 71.66% and 0.57% for Cavite, both exceeding the 70% benchmark. Batanes performed better due to its simpler landscape, while Cavite's urban complexity posed classification challenges. Comparison of recalculated RAI and iRAI values with original scores showed minimal variation. Error metrics (*MAE* = 0.52, *RMSE* = 0.65) show strong agreement and demonstrate the potential of satellite imagery as a reliable and scalable alternative for RAI/iRAI computation, offering more current insights than static census-based boundaries. However, future work should incorporate field validation to strengthen classification reliability.

3.3.3 Comparison between Regression Models: To assess the efficacy of the enhanced iRAI methodology, regression analyses were conducted using regional RAI and iRAI scores alongside three socioeconomic indicators: 1) poverty incidence, 2) percentage of population aged 5-24 not attending school, and 3) proportion of the population without access to healthcare within 30 minutes. These were sourced from PSA, APIS, and NDHS datasets.

3.3.4 Relationship between iRAI and socioeconomic factors: The iRAI regression model presented in Equation 8 showed a strong correlation (R = 0.6984, R^2 = 0.4878, p = 0.0396), indicating that nearly 49% of the variance in iRAI is explained by the independent variables (Table 3). The final model:

$$iRAI = 70.88 - (0.49)(b_1) - (3.66)(b_2) - 1.09(b_3) \quad (8)$$

Both school non-attendance (p = 0.0056) and healthcare access time (p = 0.0436) were significant predictors, while poverty incidence was not (p = 0.2749). Scenario simulation showed that improvements in these variables could increase iRAI from 6.18% to 65.72% in BARMM. Under ideal conditions, iRAI was capped at 100% after rescaling to reflect theoretical limits.

Although achieving a perfect iRAI score is desirable, the findings do not fully represent the broader context, as other factors may influence the scores. Certain unavoidable factors were not included in the regression model, making it unsafe to assume that an iRAI score of 100 conclusively indicates the ideal level of adequate accessibility to all-season roads and critical facilities. At the very least, it can be inferred that an ideal iRAI score closer to 90% may be more realistic, as it aligns with the acceptable score set by the RAI.

Variable	Coefficients	P-value	Description
Intercept	70.8812	0.0114	-
Poverty Incidence	-0.4894	0.2749	Statistically insignificant
Not Attending School	-3.6550	0.0056	Statistically significant
Access Time	1.0911	0.0436	Statistically significant

Table 3. Model Summary and Estimated Value of Predictors for the iRAI Model.

3.3.5 Relationship between RAI and socioeconomic factors: The RAI model showed weak correlation (R = 0.4050, R^2 = 0.1640, p = 0.5250), and none of the predictors were statistically significant (Table 4). Its regression equation show in Equation 9 follows a constant Y = C format, which suggests that RAI is less sensitive to socioeconomic conditions.

$$RAI = 92.27 - (0.05)(b_1) - (3.66)((b_2) + 1.09(b_3) \quad (9)$$

The results demonstrate that iRAI offers a more comprehensive and policy-relevant measure of rural accessibility than RAI, as it captures both infrastructure and service access. Its statistically significant associations with education, healthcare, and service accessibility underscore its responsiveness to socioeconomic conditions. These findings also suggest that, beyond facility distribution, underlying factors substantially influence rural accessibility outcomes. Fig. 4 illustrates the calculated provincial RAI and overall iRAI values.

Variable	Coefficients	P-value	Description
Intercept	92.2664	6.3834×10^{-9}	-
Poverty Incidence	-0.0554	0.7215	Statistically insignificant
Not Attending School	0.3037	0.4148	Statistically insignificant
Access Time	-0.1009	0.2862	Statistically insignificant

Table 4. Model Summary and Estimated Value of Predictors for the RAI Model.

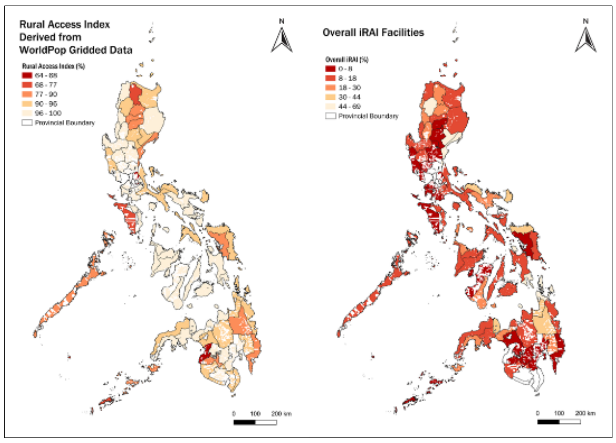

Figure 4. RAI and Overall iRAI Maps using WorldPop Gridded Population Data, by Province.

3.4 Network-Based Household-level RAI and iRAI

3.4.1 Network-Based RAI Results: The NB methodology offers a refined approach to assessing rural accessibility by using geotagged household data and actual road networks, addressing the limitations of the traditional planar buffer method.

Using OD Matrix analysis, both RAI and iRAI scores were computed for three case areas to compare traditional and NB methods. In the City of Tayabas, NB-RAI scores were generally lower. For instance, Barangay Calantas dropped from 80.72% (traditional) to 2.27% (NB-RAI), due to the absence of internal road segments (Fig. 5).

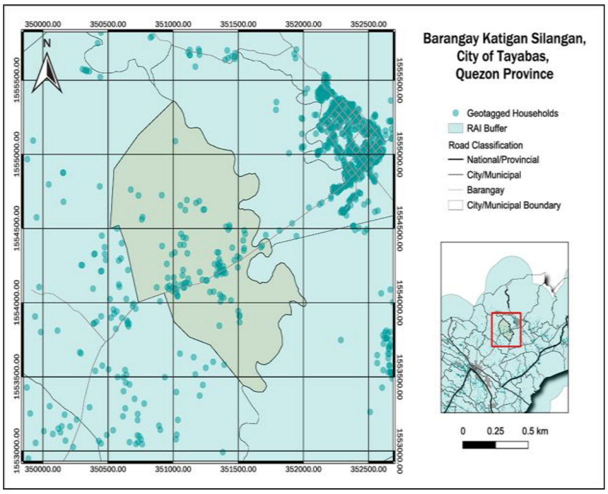

Figure 5. Buffered Road Networks in Barangay Katigan Silangan, City of Tayabas.

In contrast, Barangay Katigan Silangan showed minimal difference due to better internal connectivity, though still short of perfect due to a few disconnected households. In the Municipality of Northern Kabuntalan, NB-RAI scores were significantly higher. Seven barangays, including Montay, achieved perfect scores despite low traditional RAI values. Montay rose from 42.55% to 100%, under the NB method, including functionality of adequate roads despite limited network extent. Conversely, Barangay Gayonga dropped from 94.21% to zero percent, as households were far from the few available roads, an issue confirmed through satellite imagery (Fig. 6).

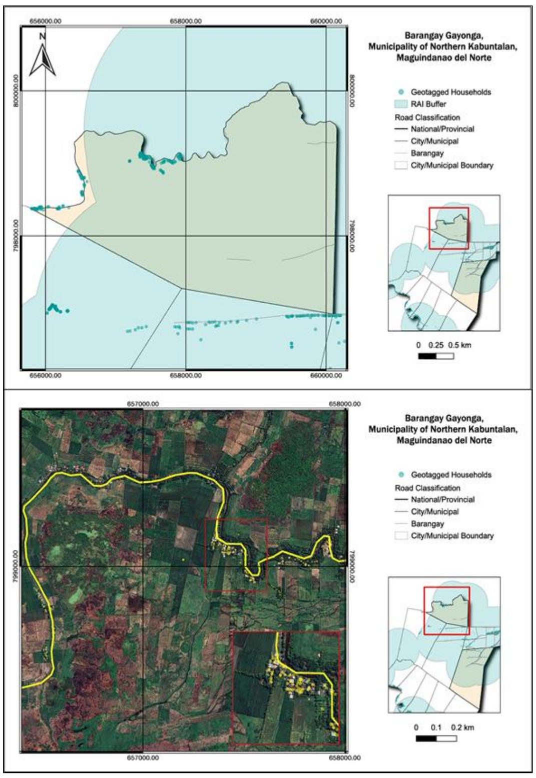

Figure 6. Buffered Road Networks and Google Satellite Imagery of Barangay Gayonga, Northern Kabuntalan.

In the Municipality of San Jose, both traditional and NB-RAI values were consistently high, with all barangays scoring 100% under the NB approach except for Barangay Cuarinta, which had a minor shortfall under the traditional method.

Overall, the NB-RAI approach produced more refined results (Table 5), especially in areas where road proximity does not equate to functional access. These findings highlight the importance of incorporating network data and actual household locations in accessibility metrics, particularly for rural development planning.

City/Municipality, Province	Barangay	RAI	NB-RAI
City of Tayabas, Quezon Province	Calantas	80.72	2.27
	Katigan Silangan	100	92
Mun. of Northern Kabuntalan, Maguindanao del Norte	Montay	42.55	100
	Gayonga	94.12	0.00
Mun. of San Jose, Dinagat Islands	Cuarinta	99.27	100

Table 5. Summarized Traditional and NB-RAI in the Three Selected Provinces.

3.4.2 Network-Based iRAI Results: The NB-iRAI approach concurrently evaluates access to healthcare, education, and service facilities, unlike the traditional method, which assesses each sector independently. In the City of Tayabas, NB-iRAI scores were generally lower than traditional scores. Around 48% of barangays showed declines, 14% improved, and 38% maintained perfect scores under both methodologies. Significant reductions were observed in Barangays Pook (from 98.14% to zero percent) (Fig. 7), Tamlong, and Domoit Kanluran. These declines were attributed to a lack of nearby facilities and inadequate road infrastructure. Conversely, Barangay Gibanga improved from 44.11% to 91.21%, owing to accessible road networks despite limited buffer coverage.

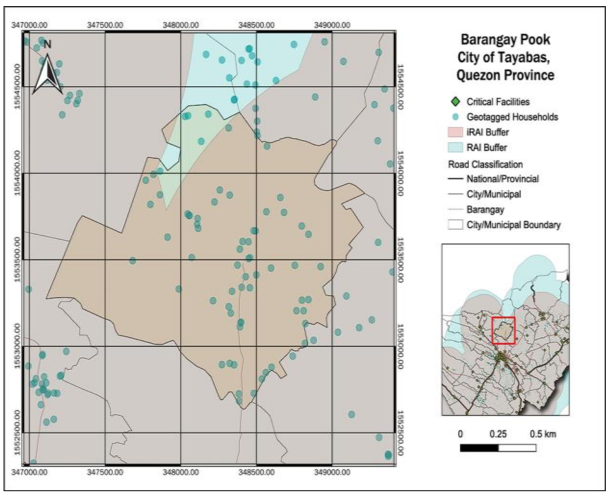

Figure 7. Buffered Road Networks and Critical Facilities in Barangay Pook, City of Tayabas.

In the Municipality of Northern Kabuntalan, over 60% of barangays recorded higher iRAI scores using the NB method. Barangays Damatog and Indatuan improved from below 5% to 100%, while Barangay Gayonga dropped to zero percent due to the absence of road access despite extensive buffer road and critical facilities coverage (Fig. 8). These results highlight how network analysis reveals access limitations not captured by planar distance methods.

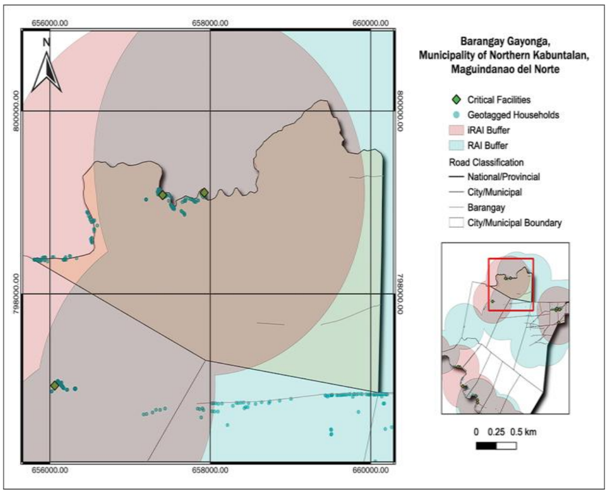

Figure 8. Buffered Road Networks and Critical Facilities in Barangay Gayonga, Northern Kabuntalan.

In the Municipality of San Jose, most barangays had perfect traditional scores. However, under the NB method, only 60% retained perfect scores, with 36% declining. Barangay Luna, for example, dropped by 23%. Table 6 details the summarized differences between the traditional and NB-iRAI scores of the selected areas. The variation across all study areas underscores the advantage of the NB methodology, which considers both spatial proximity and the actual travel path through existing road infrastructure. Unlike the traditional buffer-based method, the NB-RAI and NB-iRAI provide a more accurate and realistic representation of household accessibility to critical facilities, making it a valuable tool for infrastructure and service planning.

City/Municipality, Province	Barangay	iRAI	NB-iRAI
City of Tayabas, Quezon Province	Pook	98.14	0.00
	Tamlong	28.25	6.25
	Domoit Kanluran	100	30.77
	Gibanga	44.11	91.21
Mun. of Northern Kabuntalan, Maguindanao del Norte	Damatog	4.01	100
	Indatuan	4.43	100
	Gayonga	86.92	0
Mun. of San Jose, Dinagat Islands	Luna	100	77.03

Table 6. Summarized Traditional and NB-iRAI in the Three Selected Provinces.

Table 7 presents a summary of the RAI and iRAI variants generated in this study.

Variant	Description
RAI	Original index developed by the World Bank.
$iRAI^{HF}$	Improved RAI with integrated CBMS Healthcare Facility Data
$iRAI^{EF}$	Improved RAI with integrated CBMS Education Facility Data
$iRAI^{SF}$	Improved RAI with integrated CBMS Service Facility Data
$iRAI^{O}$	Improved RAI with integrated CBMS Healthcare, Education, and Service Facility Data
NB-RAI	Network-based RAI Computation
NB-iRAI	Network-based iRAI Computation

Table 7. Summarized RAI and iRAI variants.

4. Conclusions and Recommendations

This study advances rural accessibility measurement by enhancing the World Bank's RAI through the development of the Improved RAI. While the conventional RAI focuses solely on the proportion of the rural population living within 2 km of roads, the iRAI introduces a more multidimensional perspective by integrating accessibility to critical facilities, including healthcare centers, hospitals, schools, markets, and evacuation centers. This enhancement is particularly relevant in the Philippine context, where nearly half of the population resides in rural areas with varying levels of service provision. The findings revealed significant discrepancies between RAI and iRAI values across provinces. While 81% of provinces achieved RAI scores above 90%, iRAI values were considerably lower, highlighting facility access gaps not captured by road proximity alone. Provinces like Biliran, Camiguin, and Aurora performed well in both indices, whereas provinces such as Bataan and Occidental Mindoro recorded lower scores due to infrastructure limitations, access challenges, and incomplete CBMS facility data.

In addition, the study evaluated the use of Sentinel-2 imagery in conjunction with MLC to delineate rural areas as an alternative to static, census-based boundaries. Results demonstrated strong agreement between image-derived and official rural classifications, with error metrics indicating robust performance (MAE = 0.52, $RMSE$ = 0.65). This suggests that satellite imagery offers a scalable and timely approach to rural accessibility analysis, particularly in regions with limited or outdated census data. However, classification accuracy varied across provinces, influenced by spectral variability and cloud cover.

Regression analysis further underscored the value of the iRAI, revealing stronger correlations with key development indicators: it was negatively associated with poverty incidence and school non-attendance, and positively associated with healthcare travel time. In contrast, RAI exhibited no significant correlation with these variables. A moderate predictive model (R^2 = 0.42) was developed, and scenario-based forecasting suggested substantial potential for accessibility improvements in underserved regions such as BARMM, reinforcing the policy relevance of the enhanced index.

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To refine and expand this research, the following are recommended: (1) incorporate official and validated road condition data from relevant agencies such as the Department of Public Works and Highways (DPWH) and LGUs; (2) update and expand CBMS dataset as new rounds of geotagged facility data become available; (3) include additional socioeconomic indicators, such as employment rates and income levels, to strengthen explanatory models; and (4) enhance remote sensing methodologies by employing higher-resolution, cloud free-imagery and conducting comprehensive accuracy assessments.

This study proposed a replicable and data-driven framework for improving rural accessibility measurement. The iRAI provides a more equitable and actionable indicator, empowering policymakers and planners to identify underserved communities better, prioritize infrastructure investments and service delivery, and support initiatives such as the Ligtas Pinoy Centers Act. The insights presented in this study are critical for promoting inclusive and sustainable rural development in the Philippines and similarly situated countries.

References

Ahmed, S., Eklund, E., 2019. Rural accessibility, rural development, and natural disasters in Bangladesh. *Journal of Developing Societies*, 35(3), 391–411. https://doi.org/10.1177/0169796X19868318.

Bantang, J.A.O., San Buenaventura, P.A.R., Garraez, J.A.H., 2020. Going beyond measuring the Rural Access Index in the Philippines. *2020 Asia–Pacific Statistics Week*. Bangkok, Thailand.

CBMS Network Office, 2018. Designing poverty reduction initiatives, improving local governance, and monitoring the Sustainable Development Goals through the CBMS App.

Cornish, L., 2020. Gridded population datasets: Which one is fit for purpose? *Devex*. https://www.devex.com/news/gridded-population-datasets-which-one-is-fit-for-purpose-97212 (12 December 2024).

Cucio, J.V., Muñoz, M.N., So, O.T., 1998. A study on rural accessibility as applied to the three municipalities of Quezon Province. *Bachelor's thesis*, De La Salle University, Manila, Philippines. https://animorepository.dlsu.edu.ph/etd_bachelors/10903/ (12 December 2024).

Eqbali, S.F., Athmer, B., Asare, A., 2017. Technical paper: Rural access index – the case of Timor-Leste. *International Labour Organization (ILO)*. https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---ilo-jakarta/documents/publication/wcms_615282.pdf (23 November 2024).

Farnaz, N., Nuthammachot, N., Ali, M.Z., 2024. Comparative study of multiple algorithms classification for land use and land cover change detection and its impact on local climate of Mardan District, Pakistan. *Results in Engineering*, 21, 101131. https://doi.org/10.1016/j.rineng.2024.101131.

Khandker, S., Zaid, B., Gayatri, K., 2009. The poverty impact of rural roads: Evidence from Bangladesh. *Policy Research Working Paper 3875*, World Bank, Washington, D.C.

Kuhnle, R., 2005. *Rural infrastructure development and poverty reduction: Example of Bangladesh*. *South Asia Working Paper Series No. 49*, Asian Development Bank Institute, Manila. https://www.adb.org/sites/default/files/publication/216366/sawp-049.pdf (28 November 2024).

Miralles, M.A.O., Garraez, J.A.H., 2019. Measuring the Rural Access Index (SDG 9.1.1) for the Philippines. *International Seminar on the Use of Big Data for Official Statistics.* Hangzhou, China.

Philippine Statistics Authority, 2020. *Implementing Rules and Regulations of the Republic Act No. 11315 Otherwise Known As "Community-Based Monitoring System".* https://psa.gov.ph/cbms/ra-11315-irr (21 November 2024).

Rahman, F., Akther, M.S., Rahman, A., 2023. A study on integration of health and education facilities in Rural Access Index (RAI). *Transportation Research Interdisciplinary Perspectives*, 19, 100848. https://doi.org/10.1016/j.trip.2023.100930.

Rawat, K.S., Kumar, S., Garg, N., 2024. Statistical comparison of simple and machine learning based land use and land cover classification algorithms: A case study. *Journal of Water Management Modeling*, 32, H524. https://doi.org/10.14796/JWMM.H524.

Republic Act No. 11315, 2019. *An Act Establishing a Community-Based Monitoring System and Appropriating Funds Therefor*. Official Gazette, April 17, 2019 (Phil.).

Roberts, P., KC, S., Rastogi, C., 2006. Rural access index: A key development indicator. The International Bank for Reconstruction and Development / The World Bank, p. 2.

The World Bank Group, 2016. *Measuring Rural Access: Using New Technologies.* The World Bank, Washington, DC. https://documents1.worldbank.org/curated/en/36739147211781 5229/pdf/107996-REVISED-PUBLIC-MeasuringRuralAccessweb.pdf (2 December 2024)

van de Walle, D., & Cratty, D., 2011. Rural roads and local market development in Vietnam. *Journal of Development Studies*, 47(5), 709–734. https://doi.org/10.1080/00220381003599436.

Workman, R., & McPherson, K., 2019. Measuring rural access using new technologies: Supplemental guidelines. *ReCAP GEN2033D*. London: ReCAP for DFID. https://www.research4cap.org/wp-content/uploads/ral/Workmanetal-TRL-2019-RuralAccessIndexSupplementalGuidelines-ReCAP-GEN2033D-191219-compressed.pdf (18 December 2024).

WorldPop, 2022. WorldPop gridded population estimate datasets and tools: How are they different and which should I use? https://www.worldpop.org/methods/populations/ (15 November 2024).

Yin, X.; Li, P.; Feng, Z.; Yang, Y.; You, Z.; Xiao, C. 2021. Which gridded population data product is better? Evidences from Mainland Southeast Asia (MSEA). *ISPRS International Journal of Geo-Information*, 10(10), 681. https://doi.org/10.3390/ijgi10100681.